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Dynamic analysis of agricultural green development efficiency in China: Spatiotemporal evolution and influencing factors

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Abstract: Green development of agriculture is important for achieving coordinated and high-quality regional development for China. Using provincial data from 1990 to 2020, this work explored the dynamics of agricultural green development efficiency of 31 provinces in China, its spatiotemporal characteristics, and its driving factors using a super-efficiency slacks-based measure (Super-SBM), the Malmquist productivity index (MPI), spatial autocorrelation, and a geographic detector. Results showed that the overall agricultural green development efficiency showed a U-shaped trend, suggesting a low level of efficiency. Although a gradient difference was visible among eastern, central, and western regions, the efficiency gap narrowed each year. Technological progress and efficiency both promoted agricultural green development efficiency, especially technological progress. Agricultural green development efficiency had significant spatial aggregation characteristics, but Moran's *I* result showed a downward trend from 2015 to 2020, indicating a risk of spatial dispersion in the later stage. The provinces with high agricultural green development efficiency were mainly concentrated in the eastern region, while those with low efficiency were concentrated in the central and western regions. Agricultural green development efficiency was influenced by various factors, which showed differences according to time and region. The impact of the labor force's education level and technological progress increased during the study period, and significantly facilitated agricultural green development efficiency in the eastern region, while the central and western regions were still affected by the scale level and environmental regulation, reflecting the advantages of the eastern region in terms of economy and technology. In the future, strengthening agricultural scientific and technological innovation and deepening interprovincial cooperation can help further improve the level of green agricultural development. In addition, local governments should formulate more precise local agricultural support policies based on macro-level policies and local conditions.

Keywords: regional development; economy; technology; spatial evolution; influencing factors; super-efficiency slacks-based measure

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1 Introduction

Green development is the most important aims of China's development today. Promoting green agricultural development is a requirement for accelerating agricultural supply-side reform, an

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important measure to promote sustained agricultural development, and an area of responsibility for preserving green mountains and rivers. Although China has made considerable progress in agricultural technology and development, production continues to face challenges. For example, increasing levels of pollution and the effects of non-ecological factors have given rise to various resource and environmental problems, such as food safety issues, nonpoint source pollution, and declining soil fertility (Wang, 2020). Agriculture has replaced industry as China's largest source of pollution (Wang and Lin, 2021), making it urgent to transform agriculture to improve quality and efficiency.

Green development efficiency is the main method to measure the level of green development. The higher the efficiency of green development, the higher the level of green development. Improving such efficiency is an important way to promote the transition of society toward environmental sustainability (Xue et al., 2020; Yang et al., 2022). Researchers developed green development efficiency based on relevant international theories. Its emergence mainly stemmed from the ecological efficiency theory proposed by Schaltegger and Sturm (1990), which aims to measure the relationship between economic development and the environment. The core mission of green development is achieving the balance between economic growth, social progress, and ecological protection by regarding resources and the environment as endogenous growth factors and constructing a common, coordinated, and fair sustainable development model by changing the driving mechanism and mode of development. Correspondingly, agricultural green development efficiency is a means of minimizing pollution and the excess use of resources while ensuring the development of agricultural economy (Coluccia et al., 2020; Cui et al., 2021; Duan et al., 2021). By building an index system to measure agricultural green development, we can reflect on the effectiveness of agricultural green development (Bergius et al., 2017; Firbank, 2020). In agricultural production sectors such as dairy, olives, rain-fed farms, and rice, the agricultural green development efficiency has been widely recorded (Meul et al., 2007; Basset-Mens et al., 2009; Picazo-Tadeo et al., 2011; Gómez-Limón et al., 2012; Saber et al., 2021). Some scholars started from agricultural nitrogen efficiency (Godinot et al., 2016), agricultural water use efficiency (Todorovic et al., 2016; Akram and Mendelsohn, 2017), agricultural machinery efficiency (Hillesheim and Luxem, 2018), and other aspects to discuss the promotion mechanism of agricultural green development efficiency. In recent years, the research perspective of agricultural green development has tended to be diversified. For example, Kanter et al. (2018) studied the relationship between agricultural industrialization and agricultural green development efficiency. Colmenares and Cando (2021) and Song et al. (2022) discussed the impact of climate change on agricultural green development efficiency. Data envelopment analysis (DEA) and various improved DEA models, such as the slacks-based measure (SBM) and the Super-efficiency SBM (Super-SBM), are commonly used to measure agricultural green development efficiency (Pan and Ying, 2013; Bell et al., 2016; Lahouel, 2016; Jia and Xia, 2017). In addition, typical measurement methods include stochastic frontier analysis (Quiroga et al., 2017; Han et al., 2018), life-cycle accounting (LCA) (Rodríguez et al., 2019), the analytic hierarchy process (AHP) (Zeng and Yu, 2022), the entropy method (Chen et al., 2022), and the ecological footprint (Yang and Yang, 2019). Such methods have been employed to examine the current situation of resource utilization, evaluate results, and offer early warnings related to development (Angulo Meza et al., 2019; Richterova et al., 2021).

Research on agricultural green development efficiency in China has mainly focused on three aspects: the utilization efficiency of regional agricultural resources, the allocation efficiency of natural and social agricultural resources, and the agricultural green development efficiency under the constraints of resources and environment. Research on the utilization efficiency of regional agricultural resources has been mainly based on national, provincial, and watershed data (Wu and Song, 2018; Fu et al., 2020; Gao and Ge, 2020; Guo et al., 2021), focusing specifically on the utilization of water resources and cultivated land resources (Tong et al., 2015; Zhang et al., 2017; Xu, 2018). Research on the allocation efficiency of natural and social agricultural resources has focused on water resources, land resources, and scientific and technological resources (Deng and

Yang, 2017; Tang and Wang, 2018; Lu et al., 2022). Research on agricultural green development efficiency under environmental and resource constraints has focused on analyzing agricultural technical efficiency, agricultural production efficiency, and agricultural environmental efficiency (Cui, 2018). Topics in the literature have mainly pertained to the measurement and evaluation of efficiency (Meng et al., 2017; Tang and Wang, 2018), spatiotemporal evolution (Du and Jiang, 2020), development-oriented prediction (Song et al., 2013), and environmental impact analysis (Zeng et al., 2018).

Some gaps still exist in the research on China's agricultural green development efficiency. First, researchers have mostly focused on river basins, while few have focused on the national level. In the new era, the development model of "divide-and-rule" has great significance for regional coordinated development and improving the efficiency of green agricultural development. Given China's vast territory, it is necessary to strengthen policy formulation and implementation from the perspective of interprovincial cooperation. In addition, most studies have used cross-sectional data to study agricultural green development efficiency from a single perspective (e.g., water resource efficiency and cultivated land resource efficiency) and have seldom used panel data with a large period to measure agricultural green development efficiency, leading to a lack of analysis on the spatiotemporal distribution pattern and evolutionary regulation of agricultural green development efficiency. The comprehensive measurement of the spatiotemporal process of agricultural green development efficiency is not only conducive to assessing the past and current agricultural development status, but also can grasp the future development trend through the change in the spatial pattern. The research on agricultural green development efficiency needs to be further strengthened from the perspective of spatiotemporal evolution, combining carbon emissions, environmental pollution, and other undesirable outputs. Another weakness in the current research pertains to the measurement models. Specifically, most studies use the SBM model of unexpected output but seldom consider the further comparison of decision-making units with an efficiency of 1. It is necessary to use a Super-SBM model to offer a better solution to this problem.

Given these problems, this study aimed to offer a more diversified perspective by deploying several models, namely, the comprehensive utilization of efficiency measurement, spatial analysis, geographic detection, and comprehensively measuring interprovincial agricultural green development efficiency in China. Based on Super-SBM, we constructed a quantitative model for evaluating agricultural green development efficiency in production and considered economic input, resource input, economic output, and pollution output. We then used this model to measure agricultural green development efficiency of 31 provinces (including autonomous regions and province-level municipalities) between 1990 and 2020 in China. In addition, the MPI was used to analyze the reasons for dynamic changes in agricultural green development efficiency, spatial distribution, and evolution characteristics were examined using spatial autocorrelation analysis. Finally, we used geographic detector technology to reveal the influencing factors. In this process, we were committed to finding answers to the following questions: How does China's agricultural green development efficiency evolve? What are the spatiotemporal characteristics? What are the drivers of its growth at both production and factor levels? Attention to these issues can help promote the green development of China's agricultural economy and provide macro-level data reference for promoting China's rural revitalization strategy and high-quality development of agricultural production.

2 Materials and methods

2.1 Index system

Agricultural green development efficiency is the efficiency value between input and output, so the indicators should be selected from the perspective of input and output. The selection of indicators should accord with scientificity, availability, and systematization, and we should refer to the existing mature research when selecting indicators.

Based on previous research, we selected the number of agricultural employees, crop-sowing area, effective irrigation area, total power of agricultural machinery, and chemical fertilizer application as the input factor indicators (Pan, 2014; Wang and Zhang, 2018; Wei et al., 2018; Sun et al., 2019). The expected output indices included the total output value of agriculture, forestry, animal husbandry, and fisheries, which were converted to the constant price in 1990. Unexpected output has an adverse impact on the environment in the agricultural production process. Most scholars have considered agricultural carbon emissions or agricultural nonpoint source pollution when conducting research. Because there is a certain correlation between the two, both should be regarded as unexpected outputs in the measurement to more accurately describe the green development of agriculture. In addition, agricultural nonpoint source pollution is particularly manifested in the excessive use and residual pollution of agricultural chemicals such as chemical fertilizers, pesticides, and agricultural film. Therefore, we used the excess nitrogen (phosphorus) from chemical fertilizers and the residue of agricultural film to characterize the pollution level (Wang and Zhang, 2018; Guo et al., 2021). The indicators are shown in Table 1.

Table 1 Evaluation index of agricultural green development efficiency

Index type	Primary index	Secondary index	Index interpretation	Data sources or accounting method	Time duration
Input	Resource input	Number of agricultural employees	Labor input level of agriculture	Statistical yearbooks from 31 provinces	1990–2020
		Crop-sowing area	Land input level of agriculture	China Statistical Yearbook	
		Effective irrigation area	Construction level of agricultural water conservancy facilities		
		Total power of agricultural machinery	Agricultural mechanization level		
	Environmental input	Chemical fertilizer application	Agricultural chemistry level		
		Pesticides	Amount of pesticides used	China Rural Statistical Yearbook	
		Agricultural film	Amount of agricultural film used		
Output	Expected	Total output value of agriculture	Agricultural production		
	Unexpected	Carbon emission	Total carbon emissions from fertilizer, pesticide, agricultural film, agricultural diesel, agricultural irrigation, and agricultural planting	Li et al. (2011)	
		Nonpoint source pollution	Excess nitrogen	Guo et al. (2021)	
			Excess phosphate	Wang and Zhang (2018)	
			Residue of agricultural film	Lai et al. (2004)	

2.2 Super-SBM model

The super-SBM model was used to assess the agricultural green development efficiency. Moreover, MaxDEA is used for specific calculations. The first step in this model was to establish a possible production set of input and output, including factor input, economic growth, and emissions output, forming an efficiency analysis framework. Assuming that the production system has *n* decision-making units (DMU), namely, provinces, and each DMU contains three input–output vectors: input, expected output, and unexpected output, are respectively $x \in R^m$, $y^d \in R^{s_1}$, and $y^u \in R^{s_2}$. We can define them as three matrices X, Y^d, and Y^u, in which $X=[x_1, x_2,..., x_n] \in R^{m\times n}$, $Y^d=[y^d{}_1, y^d{}_2,..., y^d{}_n] \in R^{s_1\times n}$, and $Y^u=[y^u{}_1, y^u{}_2,..., y^u{}_n] \in R^{s_2\times n}$.

The possible production set of input and output can be defined as:

$$P=\left\{(X,Y^d,Y^u)\middle|X\geq X\lambda,\ Y^d\leq Y^d\lambda,\ Y^u\geq Y^u\lambda,\ \lambda\geq 0\right\}, \tag{1}$$

where P is the possible production set of input and output, and λ is the ideal expected input, economic growth, and emissions output of the frontier.

The second step was to build a Super-SBM containing unexpected outputs. The specific calculation formula is as follows:

$$\min\rho=\frac{\frac{1}{m}\sum_{i=1}^{m}(\bar{x}/x_{ik})}{\frac{1}{s_1+s_2}\left(\sum_{p=1}^{s_1}\bar{y}^d/y^d{}_{pk}+\sum_{q=1}^{s_2}\bar{y}^u/y^u{}_{qk}\right)},$$

$$\begin{cases}\bar{x}\geq\sum_{j=1,\neq k}^{n}x_{ij}\lambda_j;\ \bar{y}^d\leq\sum_{j=1,\neq k}^{n}y^d{}_{pj}\lambda_j;\ \bar{y}^u\geq\sum_{j=1,\neq k}^{n}y^u{}_{qj}\lambda_j\\ \bar{x}\geq x_k,\ \bar{y}^d\leq y^d{}_k,\ \bar{y}^u\geq y^u{}_k,\ \lambda_j\geq 0\\ i=1,\ 2,\cdots,\ m;\ j=1,\ 2,\cdots,\ n;\ p=1,\ 2,\cdots,\ s_1;\\ q=1,\ 2,\cdots,\ s_2\end{cases}, \tag{2}$$

where ρ is the agricultural green development efficiency; m, s_1, and s_2 are the number of input elements, expected outputs, and unexpected outputs, respectively; j and k are the DMUj and DMUk respectively; i, p and q are the values of input, expected output and unexpected output, respectively; $\bar{x}$, $\bar{y}^d$, and $\bar{y}^u$ are the relaxation vectors of input, expected output, and unexpected output, respectively; and λ is a constant vector, representing the weight of each DMU.

2.3 MPI

The MPI is generally used to measure production efficiency and decompose the change in production efficiency into two multipliers: technical progress change index (TC) and technical efficiency change index (EC) (Guan and Tan, 2014). Since the improvement of agricultural total-factor productivity (TFP) represents the improvement of agricultural productivity and industrial upgrading, and is conducive to improving agricultural green development efficiency, we used this method to analyze the contribution of TC and EC to agricultural green development efficiency. The specific model is as follows:

$$\mathrm{TFP}=\mathrm{TC}\times\mathrm{EC}, \tag{3}$$

$$\mathrm{TC}=\left[\frac{D^t(X^{t+1},Y^{t+1})}{D^{t+1}(X^{t+1},Y^{t+1})}\times\frac{D^t(X^t,Y^t)}{D^{t+1}(X^t,Y^t)}\right]^{\frac{1}{2}}, \tag{4}$$

$$\mathrm{EC}=\frac{D^{t+1}(X^{t+1},Y^{t+1})}{D^t(X^t,Y^t)}. \tag{5}$$

According to the formulas, the change value of MPI is the change value of agricultural TFP, which represents the change in productivity of a decision-making unit from t to t+1. When TFP>1, productivity shows an upward trend, and when TFP<1, productivity shows a downward trend. TFP can be decomposed into TC and EC. In the model, TC represents the contribution of the movement of the production frontier to productivity, and EC represents the contribution of the change in technical efficiency to productivity from t to t+1. With the technology of period t as reference, the output distance function of the input-output vector of period t is $D^t(X^t,Y^t)$, and with the technology of period t as reference, the output distance function of the input-output vector of period t+1 is $D^t(X^{t+1},Y^{t+1})$.

2.4 Exploratory spatial data analysis

Spatial autocorrelation is the interaction mechanism between testing element attribute values (Luc, 1995). Using global spatial autocorrelation (GSA) and local indicators of spatial association (LISA), we analyzed the spatial aggregation state of agricultural green development efficiency of 31 provinces in China, and the specific calculation was completed with GeoDA software.

$$\text{Moran's } I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(Y_i-\bar{Y})(Y_j-\bar{Y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}(Y_i-\bar{Y})}, \tag{6}$$

where n is the 31 provinces; Y_i and Y_j are the agricultural green development efficiency of provinces i and j, respectively; $\bar{Y}$ are the average value; and W_{ij} are the spatial connection matrix of provinces i and j.

We tested Moran's I according to the statistical value of Z. Its formula is as follows:

$$Z=\frac{\text{Moran's } I-E(I)}{\sqrt{\text{VAR}(I)}}, \tag{7}$$

where $E(I)$ is the expectation of the autocorrelation of the observed variable; and $\sqrt{\text{VAR}(I)}$ represents variance.

$$I_i=\frac{(Y_i-\bar{Y})}{S^2}\sum_{j=1}^{n}W_{ij}(Y_j-\bar{Y}),$$

$$S=\sqrt{\sum_{j=1,j\neq i}^{n}Y_j^2/(n-1)-\bar{Y}^2}, \tag{8}$$

where I_i is the local Moran's I of region i; positive and negative values indicate the spatial correlation degree between region i and adjacent regions. Other parameters are the same as above.

We analyzed LISA according to Moran's I scatterplot. In Moran's I scatterplot, the first quadrant represents the high efficiency level–high spatial (HH) agglomeration area. The provinces in this quadrant have a high efficiency level of agricultural green development, and are surrounded by high-level provinces. There are close links between provinces while they will generate frequent cooperation through technology, so they have a significant spatial spillover effect and form a high-level agglomeration area. The second quadrant represents the low efficiency level–high spatial (LH) agglomeration area. The provinces in this quadrant have a low efficiency level of agricultural green development but are surrounded by high-level provinces. It is a region where high-level provinces spread outward, with large regional spatial differences. The third quadrant represents the low efficiency level–low spatial (LL) agglomeration area. The provinces in this quadrant have low agricultural green development efficiency and are surrounded by low-level provinces, forming a low-level agglomeration area. The fourth quadrant represents the high efficiency level–low spatial (HL) agglomeration area. The provinces in this quadrant have high agricultural green development efficiency, but are surrounded by low-level provinces, thus forming a regional polarization effect.

2.5 Geographical exploration

To investigate the contribution of various factors to the spatial differentiation of agricultural green development efficiency, the geographic detector method takes the influencing factors as explanatory variables and the efficiency value as an explained variable (Wang et al., 2010; Wang and Xu, 2017). The formula is as follows:

$$q=1-\frac{1}{n\sigma^2}\sum_{i=1}^{k}n_i\sigma_i^2, \tag{9}$$

where i=1, 2,…; k is the stratification or partition of independent variable X and dependent variable Y; n_i and n are the number of units in layer i and the whole region, respectively; σ_i^2 and σ^2 are the variances in layer i and Y value of the whole region, respectively; and q is the effect of influencing factors on agricultural green development efficiency. The value range of q is between 0 and 1; the larger the value, the stronger the effect of the factors on agricultural green development efficiency.

3 Results and discussion

3.1 Dynamic variation of agricultural green development efficiency

As shown in Figure 1, the overall agricultural green development efficiency shows a fluctuating downward trend, which can be divided into three periods: 1990–2004, 2005–2007, and 2008–2020. From 1990 to 2004, the average value of agricultural green development efficiency showed a rapid downward trend, with values between 0.863 and 0.726, decreasing by 15.87%. The income ratio of urban and rural residents expanded from 1.8:1.0 in the 1980s to 3.1:1.0 in 2004. At this time, the main problem practitioners and policymakers faced regarding rural development was identifying ways to increase farmers' income. The difficulty of increasing farmers' income restricted the level of agricultural development and reduced farmers' enthusiasm for production. The period of 2005–2007 was characterized by a slight inverted U trend. During this period, national agricultural policies mainly focused on increasing infrastructure investment to improve agricultural productivity and competitiveness. These policies not only improved the efficiency of agricultural production but also improved the efficiency of resources and the environment in the short term. However, the effects could not be sustained. High levels of investment and resource consumption without technical support finally increased the environmental pressure and produced the abovementioned inverted U-shaped trend, in which efficiency first improved and was then weakened. However, this trend also shows that there is a lot of room for resource conservation in the process of developing agricultural sector. From 2008 to 2020, the average value of agricultural green development efficiency showed a fluctuating and slowly rising trend, with an overall increase of 4.02%. During this period, traditional agriculture continued to shift toward ecological and circular agriculture practices, and the structure of consumer demand for agricultural products gradually changed. The implementation of strategies driven by scientific and technological innovation increased investment in agricultural science and technology resources, improved the capacity for sustainable agricultural development, and contributed to the development of agricultural green development efficiency (Guo et al., 2021).

According to the differences in natural conditions, economic development level, transportation conditions, and economic benefits, the government divided China into three major economic zones: the east, the middle, and the west (Wang and Bai, 2018). The analysis results indicated that there were obvious gradient differences in efficiency values between the eastern, central, and western regions, which were ranked from high to low moving from east to west. The eastern region showed a slightly fluctuating downward trend but was generally at a medium efficiency level. This indicated that the coordination between agricultural production, environmental protection, and resource conservation was high in the eastern region. The central and western regions showed a U-shaped change. After 2014, the agricultural green development efficiency of the central region began to rise above the national average. Although efficiency in the western region was relatively low, it also increased significantly after 2014. Unlike the conclusion that some previous studies stated that the gap in agricultural green development efficiency among different regions has widened (Xue et al., 2020; Cui et al., 2021), our research demonstrates that over a larger time and space span, there are obvious gradient differences in the agricultural green development efficiency between the eastern, central, and western regions; however, these differences have shown a decreasing trend year by year. In general, there has been no "Matthew Effect" in the green development efficiency of interprovincial agriculture, but we still cannot

ignore the fluctuation of agricultural green development efficiency. Although the government has repeatedly stressed the need to balance urban and rural areas, economic development, and the coordination of resources and environment to narrow regional disparities, Chinese territory has differences in resource distribution, economic development, industrial structure, and other aspects between regions and within regions, which make it difficult to effectively reverse the long formed imbalance and disharmony between regions in a short time. At the same time, the expansion of coverage of new policy and the manifestation of the effect of policy implementation need a certain period. Therefore, according to the existing research, there is still a long way to go for all regions to achieve coordinated and balanced development in a real sense.

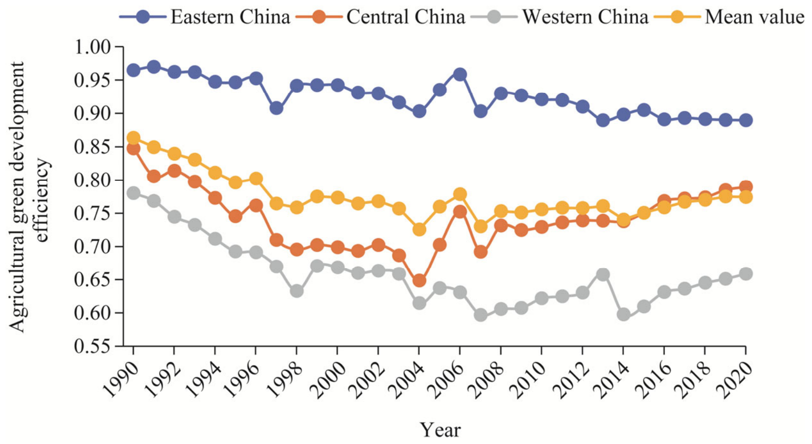

Fig. 1 Trends in agricultural green development efficiency at the national level during 1990–2020

3.2 Decomposition of agricultural green development efficiency

To further analyze the changes in trends over time, we decomposed national agricultural green development efficiency (Table 2 and Fig. 2). Overall, TFP, TC, and EC fluctuations in 31 provinces show a slow upward trend. The improvement of TFP is conducive to improving agricultural green development efficiency. The average TFP from 1990 to 2020 was 1.015, with an increase of 1.50%. The largest fluctuations in TFP occurred during 2001–2005 and 2011–2020, decreasing by 0.83% and 0.36%, respectively.

TFP decreased significantly during 2001–2005, and the prices of major agricultural products were essentially the same as, or higher than, those on the international market. Under such market conditions, raising the price of agricultural products was unlikely to increase farmers' income, which could have negatively affected their enthusiasm for production and investment. In addition, the traditional system of small-scale agriculture, which relies on the responsibility of individual household contracts, lowers the commodity rate and agricultural productivity, which cannot adequately absorb the rural surplus labor force. Illiteracy and semi-illiteracy are also high in China's rural labor force. The low quality of education available to the rural population restricts the potential adoption of new agricultural science and technologies, leading to continuous reductions in the area of cultivated agricultural land and the deterioration of the agricultural production environment.

TFP rose during 2006–2010, and governments began taking greater interest in environmental protection (Du and Jiang, 2020). In addition, government of China abolished the agricultural tax in 2006, which improved the enthusiasm of agricultural producers and improved rural access to human, material, and financial resources.

After 2011, TFP stagnated for many reasons. Affected by the 2008 global financial crisis and major weather disasters in 2009, downward pressure on domestic grain prices continued to accumulate. In response, China introduced a series of economic stimulus policies. However, many

Table 2 Decomposition of agricultural green development efficiency in 31 Chinese provinces

Province	TFP	EC	TC	Province	TFP	EC	TC
Anhui	1.022	1.004	1.018	Liaoning	1.022	0.992	1.030
Beijing	1.012	1.000	1.013	Inner Mongolia	1.002	0.991	1.013
Fujian	1.015	0.996	1.020	Ningxia	1.001	0.998	1.004
Gansu	1.006	0.997	1.009	Qinghai	1.016	0.998	1.019
Guangdong	1.016	0.993	1.024	Shandong	1.029	1.004	1.026
Guangxi	1.021	1.000	1.021	Shanxi	1.018	1.005	1.013
Guizhou	1.003	0.985	1.020	Shaanxi	1.014	0.998	1.017
Hainan	1.009	1.002	1.008	Shanghai	1.006	0.994	1.013
Hebei	1.012	0.997	1.016	Sichuan	1.013	0.994	1.019
Henan	1.016	1.002	1.014	Tianjin	1.019	0.995	1.025
Heilongjiang	1.021	1.001	1.021	Tibet	1.004	0.999	1.013
Hubei	1.016	0.992	1.025	Xinjiang	1.025	1.000	1.029
Hunan	1.007	0.993	1.015	Yunnan	1.004	0.992	1.013
Jilin	1.016	0.996	1.021	Zhejiang	1.014	0.999	1.017
Jiangsu	1.026	1.002	1.025	Chongqing	1.029	1.010	1.019
Jiangxi	1.019	0.996	1.024	Mean value	1.015	0.998	1.018

Note: TFP, total-factor productivity; EC, efficiency change index; TC, technical progress change index.

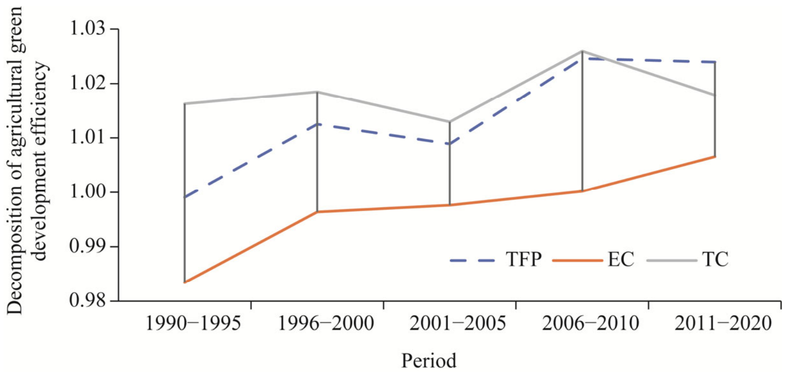

Fig. 2 Decomposition of agricultural green development efficiency during different periods. TFP, total-factor productivity; EC, efficiency change index; TC, technical progress change index.

zombie enterprises characterized by high energy consumption, high pollution, and low efficiency reemerged, resulting in excessive investment and low efficiency. In addition, with the acceleration of industrialization and urbanization, China's rural areas have faced problems such as population aging, an imperfect agricultural infrastructure, weak levels of agricultural materials and technical equipment, and an inability to withstand or mitigate disasters, leading to increasingly serious ecological problems.

The above analysis revealed that every sharp fluctuation in agricultural green development efficiency was almost accompanied by the adjustment of macro-level policies. China has made many laws related to agriculture, including policies intended to stabilize and increase grain production and ensure food security, increase farmers' nonagricultural income, and adjust the rural economic structure (Li and Qian, 2004; Zhao et al., 2022). However, many agricultural policies promote agricultural economic development, but aggravate pollution, resulting in excessive investment and low efficiency. Therefore, policymakers need to find ways to strike a balance between agricultural pollution control, food security, and farmers' income.

Regarding factor decomposition, the contribution of TC to TFP and agricultural green development efficiency was significantly greater than that of EC (Fig. 2). This indicates that agricultural productivity and agricultural green development efficiency are less dependent on resource combination, agricultural skills, and management methods than on advanced production technologies and equipment. In addition, prior to 2001–2010, TC promoted TFP, but after 2010, the promotion effect was significantly weakened, reflecting a decline in domestic research and development for new agricultural technologies and products. As suggested by some studies (Fang and Zeng, 2021; Mao et al., 2021), we believe that future policies should be based on the release of agricultural talent and emerging technologies, and should promote the synchronous improvement of agricultural productivity and agricultural green development efficiency via technological innovation.

3.3 Spatial differences in agricultural green development efficiency

Table 3 showed that Moran's *I* values were distributed in the range of 0.301–0.539, and were greater than 0.000. The *Z*-values were distributed in the range of 2.741–4.853, which all passed the *Z*-test at the 1% significance level. These results indicated that adjacent provinces had strong spatial dependence. In terms of time, Moran's *I* showed an upward trend from 1990 to 2015 and a downward trend from 2015 to 2020. This indicated that agricultural green development efficiency had significant aggregation characteristics, although there was a risk of spatial dispersion in the later stage.

Table 3 Moran's *I* values and statistical test during 1990–2020

Index	1990	1995	2000	2005	2010	2015	2020
Moran's *I*	0.305	0.385	0.399	0.509	0.517	0.539	0.301
Z-test	2.741	3.392	3.480	4.531	4.621	4.853	2.812
P	0.007	0.004	0.003	0.001	0.001	0.001	0.007

Figure 3 summarizes the distribution of each province in Moran's *I* scatterplot to clarify the correlations in local space. The three municipalities, i.e., Beijing, Tianjin, and Shanghai cities, as well as the eastern coastal provinces of Jiangsu, Zhejiang, Fujian, and Hainan, were in the HH aggregation area. With the improvement of agricultural green development efficiency, Guangdong and Shandong provinces entered the HH quadrant in 1995 and 2010, respectively. Anhui Province was in the HH quadrant, except when it entered the LH aggregation area between 1995 and 2005. Hebei and Henan provinces remained stable after entering the LH quadrant from the LL aggregation area in 1995 and 2010, respectively. Finally, Jilin, Hunan, and Hubei provinces were in the LH quadrant after experiencing fluctuations. The northwestern inland provinces (e.g., Qinghai, Sichuan, Gansu, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region, Shaanxi, and Shanxi) were in the LL quadrant. Yunnan Province, Guizhou Province, and Xinjiang Uygur Autonomous Region entered the LL quadrant in 1995. Guangxi Zhuang Autonomous Region was in the LL quadrant, except when it moved into the HL quadrant between 2010 and 2015. Heilongjiang and Liaoning provinces were in the HL aggregation area from 1990 to 2020, while Tibet Autonomous Region was in the HL quadrant from 1990 to 2005, slipping into the LL quadrant after 2005. This indicates a downward risk in agricultural green development efficiency. Chongqing City was in the HL quadrant after fluctuating between HL and LL. In general, during the study period, only Guangdong, Shandong, and Anhui provinces increased in efficiency, while Guizhou Province, Xinjiang Uygur, Tibet, and Guangxi Zhuang autonomous regions decreased.

According to the interprovincial assessments of spatial autocorrelation analysis, we found that HH was mainly distributed in eastern China. This region is characterized by rapid economic development, high-level technological innovation and management ability, rich natural resources for agriculture, and high-level development of agricultural ecology (Cao and Zeng, 2019). Modernization in this region raised agricultural green development efficiency to a high level, and

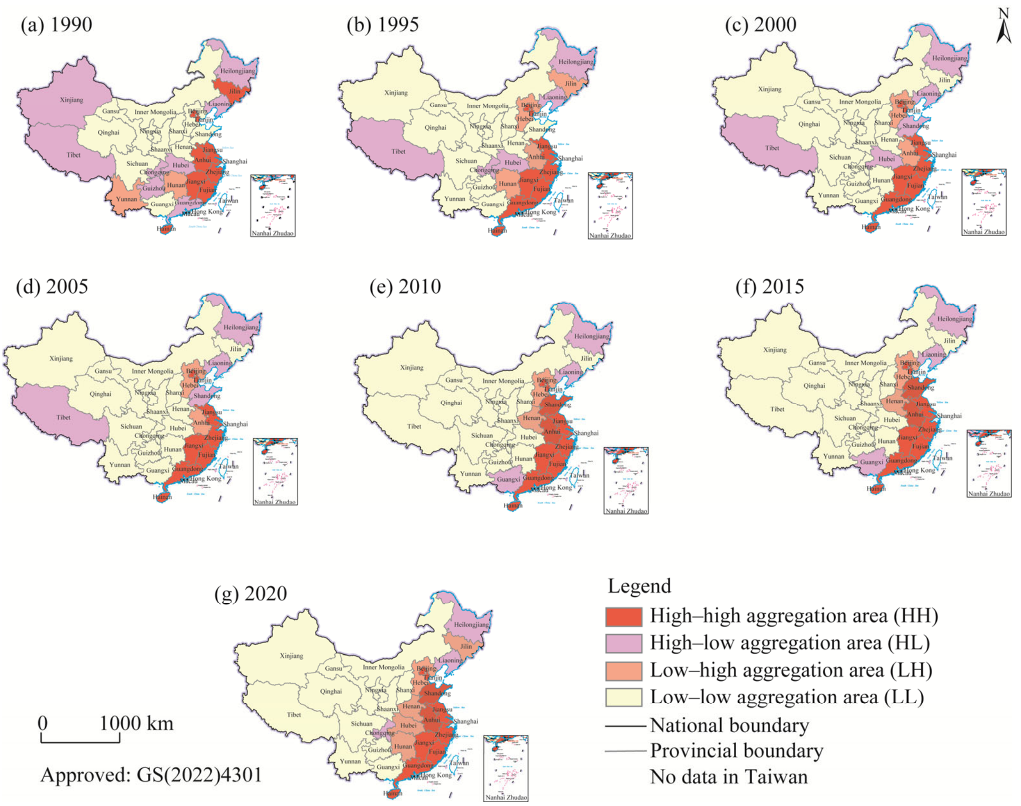

Fig. 3 Dynamic change of Moran's *I* scatterplot of agricultural green development efficiency in China. (a), 1990; (b), 1995; (c), 2000; (d), 2005; (e), 2010; (f), 2015; (g), 2020.

these advantages of agricultural development in the east have spread to the surrounding low-efficiency areas. Therefore, making use of this influence to formulate cross-regional assistance policies and strengthen the implementation of local governments can undoubtedly maintain the "catch-up effect" of agricultural green development efficiency and continuously narrow the interprovincial gap. Hebei, Henan, Hubei, and Hunan provinces, which are adjacent to the HH, leverage their own regional advantages while also taking advantage of the radiation of benefits stemming from the HH. We can expect these provinces to rise from the LH to the HH over time. The LL was mainly distributed in the central and western regions, which are major grain-producing areas. Their important agricultural status stands in sharp contrast to their fragile environments. Agricultural development is strongly dependent on natural resources, but these regions suffer from a lack of scientific planting technologies, loss of labor force (Chen et al., 2020), and low levels of agricultural green development efficiency. In contrast to their eastern counterparts, these areas have produced negative spatial spillover effects. One possible response to these negative conditions is to strengthen top-level design for the coordinated development of agricultural economy and resource conservation, and to improve the environmental awareness of agricultural production subjects. The HL was mainly distributed in northeastern China, which, with its superior production conditions and strong potential, is an advantageous area for grain production. However, this region also faces problems, such as a low degree of resource recycling and excessive consumption of water and soil resources. Radiation to surrounding areas is also relatively weak. This indicates a need to explore the optimal path for agricultural green development efficiency based on regional characteristics (Yu and Hao, 2018).

3.4 Influencing factors of agricultural green development efficiency

Agricultural green development efficiency is affected by various factors. Referring to the

literature and considering the major problems facing agricultural development (Pan, 2014; Wang and Zhang, 2018), we selected eight indicators to explore the mechanism of agricultural green development efficiency: agricultural development level, agricultural scale level, labor force's education level, financial policies for supporting agriculture, technological progress, agricultural disaster rate, environmental regulation, and agricultural industrial structure (Fig. 4). As described in Section 2.5, we used a geographic detector model to detect spatiotemporal factors in the evolution of agricultural green development efficiency. We first discretized the original data, clustered the factor values using the ArcGIS natural breakpoint method, then calculated the clustering data for 2000, 2010, and 2020 using the geographic detector, and obtained q-values of each factor, which were represented by the radar chart.

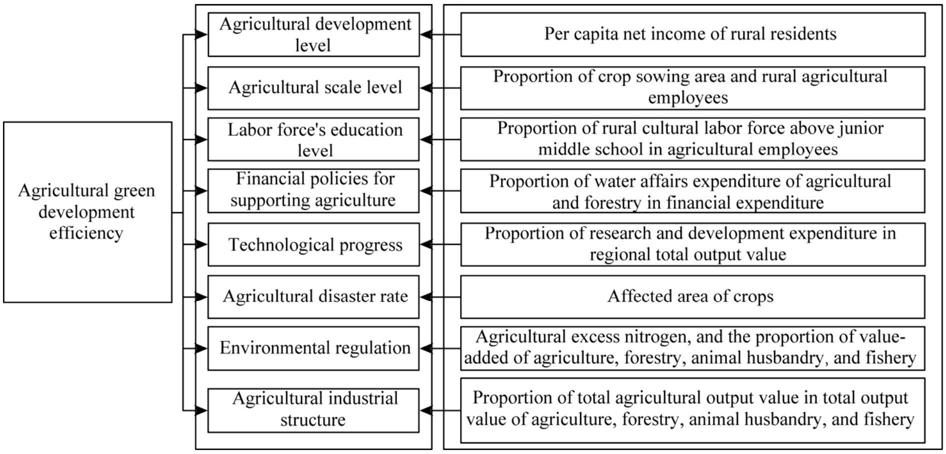

Fig. 4 Factors affecting agricultural green development efficiency

Figure 5 shows that agricultural development level, environmental regulation, and financial policies for supporting agriculture were the main factors affecting agricultural green development efficiency. In 2000, the q-values of agricultural scale level (0.020) and technological progress (0.075) were small, and had the weakest effect. In 2010, the effect of agricultural scale level (0.086) was the weakest. In 2020, the effects of agricultural scale level (0.055) and agricultural disaster rate (0.098) were the weakest. The agricultural development level was the most significant factor affecting agricultural green development efficiency, but its influence weakened year by year; the q-value decreased from 0.640 in 2000 to 0.490 in 2020. The effect of environmental regulation on agricultural green development efficiency first increased and then decreased; the q-value increased from 0.560 in 2000 to 0.630 in 2010, and then decreased to 0.580 in 2020. The q-value of financial policies for supporting agriculture decreased by 0.100 from 2000 to 2010 and by 0.120 from 2010 to 2020, indicating a declining influence. The q-value of labor force's education level increased from 0.150 in 2000 to 0.300 in 2020, and its influence continued to rise. The q-value of technological progress increased from 0.070 in 2000 to 0.300 in 2020, showing a rapidly increasing influence. The q-value of agricultural industrial structure decreased from 0.310 in 2000 to 0.250 in 2020; thus, its influence continued to decline.

The influence of a region's level of agricultural development decreased year by year, indicating that it was not positively related to agricultural green development efficiency. Improving the agricultural development level means an increase in farmers' income. However, increased income does not significantly improve technical levels but increases the input of agricultural materials, such as chemical fertilizers, to improve output, which does not have beneficial effects on agricultural green development efficiency (Zhao et al., 2022). The effect of environmental regulation showed a trend of first rising and then falling. In the early stage of agricultural development, agricultural output and income growth are mainly promoted by consuming natural resources and increasing the input of social factors, while the growth mode is relatively extensive. At that time, environmental regulation significantly improves the environmental efficiency of

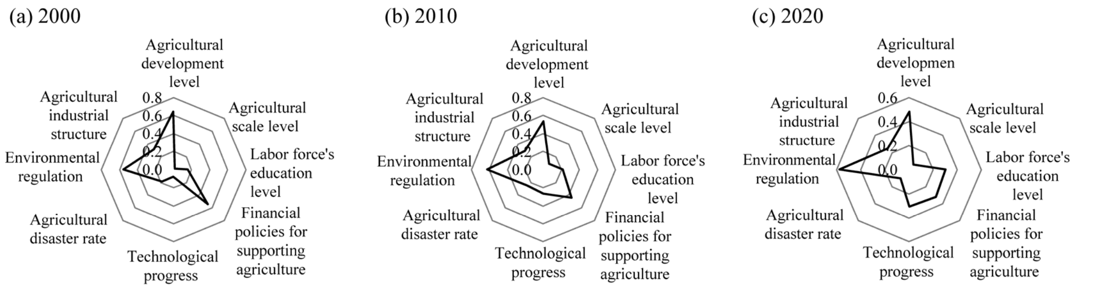

Fig. 5 Radar chart of factors affecting agricultural green development efficiency. (a), 2000; (b), 2010; (c), 2020.

agricultural resources. With improvements in the economy, technology, and environmental awareness, agricultural production increased its dependence on advanced management methods, and the role of environmental regulation was weakened. Although macro-level policy adjustments had a significant effect on agricultural green development efficiency, the influence of local financial support policies declined, indicating that the formulation of local policies was not sufficiently specific or accurate. A lack of information about farmers' preferences for agricultural public goods during policy formulation often causes the financial expenditure structure for supporting agriculture deviate from social demand (Li and Qian, 2004). Additionally, the effect of agricultural industrial structure on agricultural green development efficiency also declined, which indicates that the effect of agricultural industrial transformation has not been significant in recent years, especially judging from the situation of agricultural development in some central and western regions. However, the development of leisure agriculture and ecological agriculture needs to be further explored (Hu and Zhong, 2019).

During the study period, factors such as the education level of labor force and technological progress had an increasing influence on agricultural green development efficiency. A higher level of education in the labor force was found to be conducive to agricultural modernization. Education improves, for example, the labor force's capacity to master more advanced science and technology, effectively use market information, and interpret policy. Overall, improving the labor force's education level is conducive to promoting large-scale production, optimizing the allocation of resources, increasing employment opportunities, and promoting rural development. The influence of technological progress on agricultural green development efficiency also increased rapidly. With improved levels of socioeconomic development, technological progress becomes an inevitable demand of agricultural development. At present, agricultural development aims to not only reduce back-end costs in the industrial chain but also satisfy consumer demand regarding the quality and characteristics of agricultural products. In this regard, technological progress plays an important role in the production, processing, and sale of agricultural products.

Then, by dividing 31 provinces into three regions: eastern China, central China, and western China, taking 2020 as an example, we analyzed regional differences in the influencing factors. From a spatial perspective (Table 4), the agricultural development level, technological progress, and agricultural industrial structure had significant effects on agricultural green development efficiency in the eastern region. In the central region, the agricultural disaster rate and agricultural industrial structure had less impact while the effects of other factors were more significant. Agricultural green development efficiency in western China was mainly restricted by environmental regulation and agricultural development level. This result supports the analysis of spatial autocorrelation to some extent and also reflects the advantages of eastern region in the economy, technology, and ideas. Although agriculture is not a leading industry in the region, regional characteristics such as a strong advocacy for environmental protection, and the adoption of agricultural science and technology allow for the rapid development of efficient. The secondary industry is dominant in the central region, providing the basic machinery needed to develop agricultural production, while also bringing enormous pressure on resources and environment. In western region, most regions have small-scale decentralized operations in arid

hilly areas. Because the environment is generally fragile and the labor force's education level is low, agricultural green development efficiency is still unable to eliminate the impact of environmental regulation.

Table 4 Zoning detection results for the factors affecting agricultural green development efficiency in 2020

Factor	Region			
	Eastern China	Central China	Western China	China
Agricultural development level	0.726	0.805	0.645	0.485
Agricultural scale level	0.185	0.570	0.549	0.055
Labor force education level	0.267	0.558	0.103	0.304
Financial policies for supporting agriculture	0.095	0.429	0.410	0.321
Technological progress	0.479	0.492	0.514	0.304
Agricultural disaster rate	0.432	0.116	0.246	0.099
Environmental regulation	0.236	0.792	0.631	0.581
Agricultural industrial structure	0.415	0.105	0.382	0.251

3.5 Suggestions for improving agricultural green development efficiency in China

Based on our findings and in consideration of current national strategies, we offer the following suggestions for improving agricultural green development efficiency in China: (1) strengthening scientific and technological innovation in the agricultural sector and improving the technical level of agricultural production. Promoting the integration of scientific and technological forces and resource sharing, and fostering innovative elements such as talent, capital, information, and technology. Promoting the transformation of the agricultural development mode through scientific and technological innovation. Guiding agriculture in the development of products and processes that are green of high quality and well branded. Such measures will help form a high-quality, efficient, and dynamic modern agricultural industrial system; (2) governments at all levels should aim to fully grasp the spatial correlations of interprovincial agricultural green development efficiency in China. They should pay attention not only to the impact of attribute data on agricultural green development efficiency but also to the role of relationship data. Agricultural green development efficiency in China has shown a development trend of high in the east, low in the west, high in the south, and low in the north. Policies should therefore give play to the pivotal role of the network's core node and strengthen interconnections and interactions between underdeveloped areas and those with high agricultural green development efficiency. Channels should be created to facilitate the interprovincial flow of green agricultural production factors, strengthen interprovincial scientific and technological cooperation, and build an agricultural science and technology innovation alliance. Governments should also seek to improve China's agricultural green development efficiency through collaborative innovation; and (3) based on macro-level policies, local governments should formulate more local agricultural support policies in consideration of local situation. This involves accurately implementing policies, establishing incentive mechanisms for agricultural development, and improving environmental and resource efficiency. The efficient use of agricultural support funds should also be supported to promote advanced grain production technology and avoid rural polarization caused by inefficient policies. For the western region, financial support for agriculture should not only enhance input factors and infrastructure but also promote new agricultural technologies, equipment, and management methods. Social factors should also be considered in western region, such as the culture of ethnic minorities, tourism, and current agricultural development, to provide better conditions for further agricultural development.

3.6 Limitations

This study revealed the long-term evolution characteristics and spatial differentiation of green agricultural development, which can provide guidance for green agricultural development in

China at macro-level. It should be noted that in the future, the evaluation of agricultural green development efficiency should be spatially enriched, and it is particularly necessary to conduct special research on western region. Moreover, macro-level evaluation should be checked against that of micro-level. In terms of index selection, with the ongoing development of field research and the improvement of data availability, the selection of input and output elements can be further refined. In addition, in the descriptive statistical analysis of agricultural green development efficiency in 31 provinces, we found many outliers in four provinces and cities–namely, Beijing City from 1996 to 1998, Shanghai City from 2012 to 2017, Guizhou Province from 1990 to 1992, and Yunnan Province from 1990 to 1993. The outliers in Beijing and Shanghai cities were lower than those in other years while the outliers in Guizhou and Yunnan provinces were higher than those in other years. In future research, enhancing the analysis of outliers could yield a more accurate understanding of the mechanism for improving the agricultural green development efficiency.

4 Conclusions

This study measured the agricultural green development efficiency of 31 provinces in China from 1990 to 2020. We used a Super-SBM model and decomposed agricultural green development efficiency, analyzed spatial correlations based on MPI and global Moran's *I*, and examined the factors affecting interprovincial agricultural green development efficiency. The conclusions are as follows: (1) the overall agricultural green development efficiency of 31 provinces was low during the study period, it first trended downward and then curved back up. There were obvious gradient differences in agricultural green development efficiency between China's eastern, central, and western regions. The eastern region had the highest efficiency, followed by central region and western region, which had the lowest efficiency. This gap between different regions, however, narrowed year by year. The MPI analysis showed gradual increases in the fluctuation of TFP. While technological progress and efficiency both promoted the improvement of agricultural green development efficiency, the main driving force was related to changes in technological progress; (2) agricultural green development efficiency showed significant aggregation characteristics during the study period, although there was a risk of spatial dispersion in the later part of the study period. The HH areas were mainly distributed in eastern region with high levels of agricultural technological innovation. The LL areas were mainly distributed across the central and western regions, which had poor environmental conditions. The spatial distribution structure can thus be described as high-efficiency and high-radiation in the east, and low-efficiency and low-radiation in the west; and (3) agricultural green development efficiency was affected by various factors. From the perspective of time dimension, the level of agricultural development, environmental regulation, and financial support for agriculture were consistently the main factors affecting agricultural green development efficiency, while the influence of the labor force's education level and technological progress increased during the study period. From a spatial perspective, the levels of agricultural development, technological progress, and agricultural industrial structure had a significant impact in the east, while the central and western regions were still affected by various factors such as the scale level and environmental regulation, reflecting the advantages of the east in terms of economy and technology. Thus, interprovincial cooperation is urgently needed to further promote the development of green agriculture.

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References

Akram A A, Mendelsohn R. 2017. Agricultural water allocation efficiency in a developing country canal irrigation system. Environment and Development Economics, 22(5): 571–593.

Angulo-Meza L, Gonzalez-Araya M, Iriarte A, et al. 2019. A multiobjective DEA model to assess the eco-efficiency of agricultural practices within the CF plus DEA method. Computers and Electronics in Agriculture, 161: 151–161.

Basset-Mens C, Ledgard S, Boyes M. 2009. Eco-efficiency of intensification scenarios for milk production in New Zealand. Ecological Economics, 68(6): 1615–1625.

Bell A, Parkhurst G, Droppelmann K, et al. 2016. Scaling up pro-environmental agricultural practice using agglomeration payments: Proof of concept from an agent-based model. Ecological Economics, 126: 32–41.

Bergius M, Benjaminsen T A, Widgren M. 2017. Green economy, Scandinavian investments and agricultural modernization in Tanzania. Journal of Peasant Studies, 45(4): 825–852.

Cao J W, Zeng K. 2019. Study on agricultural eco-efficiency and its influencing factors in the Yangtze River economic belt from the perspective of low carbon. Ecological Economy, 35(8): 115–119, 127. (in Chinese)

Chen J Q, Xin M, Ma X J, et al. 2020. Chinese agricultural eco-efficiency measurement and driving factors. China Environmental Science, 40(7): 3216–3227.

Chen Z, Sarkar A, Rahman A, et al. 2022. Exploring the drivers of green agricultural development (GAD) in China: A spatial association network structure approaches. Land Use Policy, 112: 105827, doi: 10.1016/j.landusepol.2021.105827.

Colmenares I E P, Cando L J R. 2021. Eco-efficiency of the models of agricultural production of hard corn and its influence on climate change in Shushufindi Ecuador. Granja, 33: 76–91.

Coluccia B, Valente D, Fusco G, et al. 2020. Assessing agricultural eco-efficiency in Italian regions. Ecological Indicators, 116: 106483, doi: 10.1016/j.ecolind.2020.106483.

Cui X. 2018. Research on the measurement of agricultural production efficiency and the influencing factors under the constraints of resources and environment. PhD Dissertation. Changchun: Jilin University. (in Chinese)

Cui Y, Liu W X, Cai Y, et al. 2021. Has the efficiency of rural green development converged in China?–An empirical analysis from 1997 to 2017. Journal of Agrotechnical Economics, 22(2): 72–87. (in Chinese)

Deng M H, Yang C X. 2017. Analysis on the dynamic evolution of agricultural science and technology resources allocation efficiency based on super efficiency DEA model. Chinese Journal of Agricultural Resources and Regional Planning, 38(11): 61–66. (in Chinese)

Du H M, Jiang L. 2020. Research on the spatial and temporal disparity of agricultural ecological efficiency of Dongting Lake area based on SE-SBM model. Ecological Economy, 36(4): 100–106, 121. (in Chinese)

Duan H B, Feng K S, Tong F. 2021. Climate change mitigation and green transformation in China. Regional Environmental Change, 21: 110.

Fang Y L, Zeng X L. 2021. Evaluation and improvement of agricultural eco-efficiency in China. Journal of Agricultural Resources and Environment, 38(1): 135–142. (in Chinese)

Firbank L G. 2020. Towards the sustainable intensification of agriculture–a systems approach to policy formulation. Frontiers of Agricultural Science and Engineering, 7(1): 81–89.

Fu L L, Mao X H, Mao X B, et al. 2020. Research on evaluation of the green agriculture development in Zhejiang Province under the background of rural revitalization–from the perspective of comprehensive utilization of agricultural resources. Chinese Journal of Agricultural Resources and Regional Planning, 41(12): 23–34. (in Chinese)

Gao J, Ge Z H. 2020. Regional difference and trend analysis of agricultural green development level in Jiangsu Province. Chinese Journal of Agricultural Resources and Regional Planning, 41(12): 14–22. (in Chinese)

Godinot O, Leterme P, Vertes F, et al. 2016. Indicators to evaluate agricultural nitrogen efficiency of the 27 member states of the European Union. Ecological Indicators, 66: 612–622.

Gómez-Limón J A, Picazo-Tadeo A J, Reig-Martínez E. 2012. Eco-efficiency assessment of olive farms in Andalusia. Land Use Policy, 29(2): 395–406.

Guan J B, Tan Y W. 2014. Analysis of the impact of seed subsidy on cotton production efficiency in China. Journal of Agrotechnical Economics, 32(3): 49–56. (in Chinese)

Guo X J, Zhou R, Li J Z, et al. 2021. Spatial-temporal evolution characteristics and influencing factors of agricultural resources and environment efficiency in the Yellow River Basin. Journal of Ecology and Rural Environment, 37(3): 332–340. (in Chinese)

Han Z X, Liu D H, Chang X Y. 2018. Measurement of China's agricultural production efficiency and analysis of its regional differences based on SFA. Jiangsu Agricultural Sciences, 46(23): 388–392. (in Chinese)

Hillesheim T, Luxem A. 2018. Increased efficiency of agricultural machines through aluminum storage cylinders. ATZ Offhighway Worldwide, 11: 34–37.

Hu P B, Zhong Y P. 2019. The mechanism of improving agricultural eco-efficiency by the integration of agriculture and tourism supported by the government: Taking the national leisure agriculture and rural tourism demonstration counties as an example.

Chinese Rural Economy, 35(9): 85–104. (in Chinese)

Jia L, Xia Y. 2017. Scale efficiency of grain production and influencing factors based on survey data from Heilongjiang, Henan and Sichuan. Resources Science, 39(5): 924–933. (in Chinese)

Kanter D R, Musumba M, Wood S L R, et al. 2018. Evaluating agricultural trade-offs in the age of sustainable development. Agricultural Systems, 163: 73–88.

Lahouel B B. 2016. Eco-efficiency analysis of French firms: A data envelopment analysis approach. Environmental Economics and Policy Studies, 18(3): 395–416.

Lai S Y, Du P F, Chen J N. 2004. Evaluation of non-point source pollution based on unit analysis. Journal of Tsinghua University: Science and Technology, 9(3): 1184–1187.

Li B, Zhang J B, Li H P. 2011. Research on spatial-temporal characteristics and affecting factors decomposition of agricultural carbon emission in China. China Population, Resources and Environment, 21(8): 80–86. (in Chinese)

Li H Z, Qian Z H. 2004. A causal and structural analysis of the relationship between fiscal support policies and agricultural growth in China. Chinese Rural Economy, 20(8): 38–43. (in Chinese)

Lu C P, Ji W, Hou M C, et al. 2022. Evaluation of efficiency and resilience of agricultural water resources system in the Yellow River Basin, China. Agricultural Water Management, 266: 107605, doi: 10.1016/j.agwat.2022.107605.

Luc A. 1995. Local indicators of spatial association: LISA. Geographical Analysis, 27(2): 93–115.

Mao H, Zhou L, Ying R Y, et al. 2021. Time preferences and green agricultural technology adoption: Field evidence from rice farmers in China. Land Use Policy, 109: 105627, doi: 10.1016/j.landusepol.2021.105627.

Meng J J, Wang J W, You N S, et al. 2017. Spatiotemporal differentiation of water allocation efficiency in oasis irrigated areas in the middle reaches of the Heihe River. Research of Soil and Water Conservation, 24(1): 173–180. (in Chinese)

Meul M, Nevens F, Verbruggen I, et al. 2007. Operationalising eco-efficiency in agriculture: the example of specialised dairy farms in Flanders. Progress in Industrial Ecology, 4(1–2): 41–53.

Pan D, Ying R Y. 2013. Agricultural eco-efficiency evaluation in China based on SBM model. Acta Ecologica Sinica, 33(12): 3837–3845.

Pan D. 2014. Evaluation and determinants of agricultural green productivity in China. Forum on Science and Technology in China, 29(11): 149–154. (in Chinese)

Picazo-Tadeo A J, Gómez-Limón J A, Reig-Martínez E. 2011. Assessing farming eco-efficiency: A data envelopment analysis approach. Journal of Environmental Management, 92(4): 1154–1164.

Quiroga S, Suárez C, Fernández-Haddad Z, et al. 2017. Levelling the playing field for European Union agriculture: Does the common agricultural policy impact homogeneously on farm productivity and efficiency? Land Use Policy, 68: 179–188.

Richterova E, Richter M, Sojkova Z. 2021. Regional eco-efficiency of the agricultural sector in V4 regions, its dynamics in time and decomposition on the technological and pure technical eco-efficiency change. Equilibrium, 16: 553–576.

Rodríguez C M, Rengifo Rodas C F, Corrales Muñoz J C, et al. 2019. A multi-criteria approach for comparison of environmental assessment methods in the analysis of the energy efficiency in agricultural production systems. Journal of Cleaner Production, 228: 1464–1471.

Saber Z, van Zelm R, Pirdashti H, et al. 2021. Understanding farm-level differences in environmental impact and eco-efficiency: the case of rice production in Iran. Sustainable Production and Consumption, 27: 1021–1029.

Song M L, Zhang L L, An Q X, et al. 2013. Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002-2010-2012. Journal of Cleaner Production, 42: 42–51.

Song Y G, Zhang B C, Wang J H, et al. 2022. The impact of climate change on China's agricultural green total factor productivity. Technological Forecasting and Social Change, 185: 122054, doi: 10.1016/j.techfore.2022.122054.

Sun W L, Wang R B, Jiang Q, et al. 2019. Study on connotation and evaluation of the agricultural green development. Chinese Journal of Agricultural Resources and Regional Planning, 40(4): 14–21. (in Chinese)

Tang L J, Wang D Y. 2018. The efficiency loss of county-level land resource allocation its optimization paths. Ecological Economy, 34(9): 111–115.

Todorovic M, Mehmeti A, Scardigno A. 2016. Eco-efficiency of agricultural water systems: Methodological approach and assessment at meso-level scale. Journal of Environmental Management, 165: 62–71.

Tong J P, Ma J F, Wang S, et al. 2015. Research on agricultural water use efficiency in Yangtze River Basin based on super-efficiency DEA and Tobit model. Resources and Environment in the Yangtze Basin, 24(4): 603–608. (in Chinese)

Wang B Y, Zhang W G. 2018. Cross-provincial differences in determinants of agricultural eco-efficiency in China: An analysis based on panel data from 31 provinces in 1996–2015. Chinese Rural Economy, 34(8): 46–62. (in Chinese)

Wang F H, Ma W Q, Dou Z X, et al. 2006. The estimation of the production amount of animal manure and its environmental effect in China. China Environmental Science, 26(5): 614–617. (in Chinese)

Wang F P, Bai W G. 2018. Study on the coordinated development of agricultural modernization, new industrialization and urbanization–Panel analysis based on China's three major economic zones in 1998–2015 years. Lanzhou Academic Journal, 38(5): 200–208. (in Chinese)

Wang H F. 2020. Temporal and spatial analysis of county agricultural efficiency in Anhui Province based on SSBM-ESDA model. Economic Geography, 40(4): 175–183, 222.

Wang J, Li X, Christakos G, Liao Y L, et al. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. International Journal of Geographical Information Science, 24(1): 107–127.

Wang J F, Xu C D. 2017. Geodetector: Principle and prospective. Acta Geographica Sinica, 72(1): 116–134.

Wang S Y, Lin Y J. 2021. Spatial evolution and its drivers of regional agro-ecological efficiency in China's from the perspective of water footprint and gray water footprint. Scientia Geographica Sinica, 41(2): 290–301.

Wei Q, Zhang B, Jin S Q. 2018. A study on construction and regional comparison of agricultural green development index in China. Issues in Agricultural Economy, 467(11): 11–20. (in Chinese)

Wu C Q, Song Z Y. 2018. Study on the measurement and affecting factors of agricultural green total factor productivity in the Yangtze River economic belt. Science & Technology Progress and Policy, 35(17): 35–41. (in Chinese)

Xu Y F. 2018. Study on agricultural resources utilization efficiency in Shanxi Province based on DEA model. Journal of Shanxi Agricultural University: Social Science Edition, 17(4): 55–61. (in Chinese)

Xue L, Shen Y, Xu C H. 2020. A research on spillover effects of agricultural agglomeration on agricultural green development efficiency. Economic Survey, 37(3): 45–53. (in Chinese)

Yang L, Yang Y T. 2019. Evaluation of eco-efficiency in China from 1978 to 2016: Based on a modified ecological footprint model. Science of the Total Environment, 662: 581–590.

Yang T, Zhou K L, Zhang C. 2022. Spatiotemporal patterns and influencing factors of green development efficiency in China's urban agglomerations. Sustainable Cities and Society, 85: 104069, doi: 10.1016/j.scs.2022.104069.

Yu T, Hao X B. 2018. Evaluation and analysis on the temporal and spatial characteristics of agricultural eco-efficiency of major grain production. Ecological Economy, 34(9): 104–110. (in Chinese)

Zeng C L, Yu L. 2022. Do China's modern agricultural demonstration zones work? Evidence from agricultural products processing companies. Applied Economics, 54(37): 4310–4323.

Zeng Y T, Lv Y R, Wang X R. 2018. Multi-dimensional analysis of farmland circulation's effect on technical efficiency of grains' production: An empirical study based on Stochastic Frontier Analysis. Journal of Huazhong Agricultural University: Social Sciences Edition, 133(1): 13–21, 156–157. (in Chinese)

Zhang L X, Zhu D L, Xie B P, et al. 2017. Spatiotemporal pattern evolvement and driving factors of cultivated land utilization efficiency of the major grain producing area in China. Resources Science, 39(4): 608–619. (in Chinese)

Zhao J, Dang G Y, Tang X J. 2022. Spatial-temporal differences and influencing factors of agricultural eco-efficiency in China based on SBM-Tobit model. Journal of Southwest Forestry University: Social Sciences, 6(6): 10–18. (in Chinese)